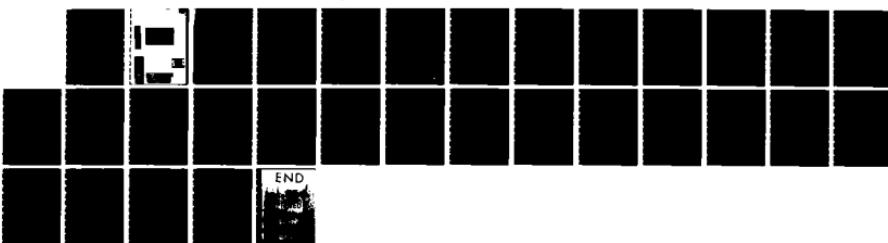


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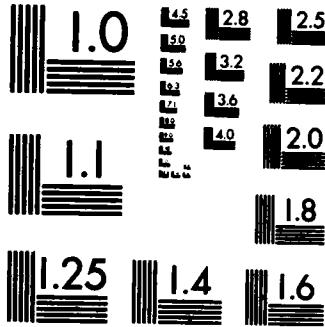
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**A Cross-Study Analysis of
Covariation Judgments**

**Marlys Gascho Lipe
University of Chicago
Graduate School of Business
Center for Decision Research**

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in order to mitigate the effects of specific characteristics, and a lens model analysis is done.

It is found that subject achievement is high in the covariation task as opposed to tasks used in other lens model studies. However, subjects did not use all of the available information to the extent specified in the statistical covariation model. The normativeness of this model is questioned.

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A Cross-Study Analysis of Covariation Judgments

Maryse Gascho Lipe

Crocker (1981a) summarized a recent review of covariation judgments by stating "Evidence has accumulated indicating that intuitive covariation judgments are subject to several sources of bias. In all likelihood, our conceptions of our social world which are based on these judgments are simply incorrect much of the time." (p. 288)

Crocker's paper is an illuminating review of the individual studies that have been conducted regarding covariation judgments. However, her analysis could be profitably supplemented with research on what these individual studies reveal when taken as a whole. The purpose of this note is to present such an overview by providing a cross-study analysis of covariation judgments.

Crocker notes several conditions that can affect the accuracy of covariation judgments. These include characteristics of the task, characteristics of the data, and characteristics of the perceiver. Any of these aspects, it is argued, could cause subjects to systematically over- or under-estimate the correlation relative to that actually present in a given task. Therefore, any single study will contain such confounding factors thereby limiting the generalizability of its conclusions. The present project uses data from 5 different studies in order to draw conclusions that can be generalized more readily to a range of situations.

The usual covariation study presents subjects with data from the four cells of a 2X2 table (for an example, see Fig. 1) either instance-by-instance or in summary form. A common finding is that, relative to the normative statistical model of correlation, cell A receives too much weight in subjects' judgments (Smedslund, 1963; Jenkins & Ward, 1965; Alloy & Abramson, 1979). Also, disconfirming evidence, cells B and C, receive too little weight, and cell D is virtually ignored. Crocker (1981b) found similar results when she tried an unusual task format, having subjects request the cell data necessary to make judgments of covariation.

The proposition that subjects do not use disconfirming evidence has been the subject of much study. However, the results of this research have been quite inconsistent and, contrary to the studies cited above, several authors have concluded that subjects do not use decision rules based exclusively on cell A (Ward & Jenkins, 1965; Shaklee & Mims, 1981; Sessie & Endersby, 1972). Ward and Jenkins (1965) and Shaklee and Mims (1981), for example, analyzed each subject's judgments individually and concluded that subjects used sophisticated rules for judging covariation. Furthermore, Sessie and Endersby (1972) have raised the issue that covariation judgments may not be very informative in themselves. Hence, they asked their subjects to make decisions based on the cell data, rather than asking for judgments of correlation. Results showed that Sessie and Endersby's subjects made decisions that were consistent with the normative model of correlation. However, we cannot know what judgmental rule these subjects were actually using. They may, in fact, have used a much simpler model, such as conditional

probabilities or some linear combination of the cell data.

The conclusions of these latter studies contrast sharply with the frequently cited assertion that "normal adults with no training in statistics do not have a cognitive structure isomorphic with the concept of correlation." (Smedslund, 1963, p. 172.) However, such contradictory findings should come as no surprise given Crocker's statements about the importance of task characteristics and their effects on experimental results. It is possible that any result could be obtained given the appropriate combination of task characteristics, data characteristics, and perceiver traits. Of course we are more interested in conclusions that can be widely generalized. Thus, it would be informative to see how heavily each kind of cell information is weighted over a range of situations, when task characteristics are varied.

Method

As previously stated, this research used data from 5 studies. Other studies simply did not provide the necessary information for inclusion in this project. The studies used and the number of data points taken from each are listed in Table 1, along with the context that was used in each task. Each "data point" consists of cell frequencies and the average judged covariation based on those cells. For example, one data point was:

Cell A	B	C	D	Judgment
23	2	7	18	.79

(Complete data sets may be obtained from the author.) Because the studies used different judgment scales, these were standardized to a percentage basis (e.g., 3.7 on a 5-point scale was converted to 3.7/5, or 74%).

The formula for correlation based on a 2x2 joint frequency table is a complex nonlinear function of the four cell entries, namely:

$$\text{corr} = (AD - BC) / \sqrt{(A+B)(C+D)(A+C)(B+D)}.$$

Although this equation is known to the experimenter in any given study, it is not clear whether it would be known to the subjects nor whether the subjects could use such a formula without computational aids. Thus, using such a model as a benchmark may be an unfair or inappropriate method of assessing subjects' abilities at covariation tasks. For this reason the "lens model" framework (Hursch, Hammond, & Hursch, 1964) is a useful methodology for this project. In essence, the lens model assumes that the actual correlational model is unknown or unavailable. However, the experimenter is able to build a linear model of correlation using the cell frequencies as variables in the model. By also building a linear model of the subjects' judgments, the experimenter can make an assessment of the subjects' abilities at the task, while using a simple linear benchmark.

Thus, the three important components of the lens model are the cell data (A, B, C, D), the actual correlation as computed using the cell data (Y_e), and the correlation as estimated by the subjects (Y_s). These are used in two multiple regression equations, one of which models the environment while the other models the judgments of the subjects. Therefore, the following regressions were run using data

from the five studies listed in Table 1:

$$Y^*e = K + \alpha_1 A + \alpha_2 B + \alpha_3 C + \alpha_4 D \quad (1)$$

$$Y^*s = K' + \alpha'_1 A + \alpha'_2 B + \alpha'_3 C + \alpha'_4 D \quad (2)$$

The correlation matrix was also calculated in order to obtain the following measures:

R_e = the correlation between Y_e and Y^*e . This is a measure of the linear predictability of the criterion Y_e .

R_s = the correlation between Y_s and Y^*s . This is analogous to R_e above and measures the linear predictability of the judge or subjects.

G = the correlation between Y^*e and Y^*s . This is a measure of the degree to which the regression equations of the subjects and the environment match.

C = the correlation between the residuals of the two regression models. This is a measure of the degree of match of the nonlinear portion of the subjects' judgments and the nonlinearity in the environment.

r_a = the correlation between Y_e and Y_s . This denotes the subjects' achievement.

R_n = the correlation between Y^*e and Y_s . This is a measure of the subjects' achievement assuming the linear model of the environment is used as a normative model.

These measures also allow comparisons of subjects' achievement in this task with subjects' achievement in other situations (see Camerer, 1981).

Results

Regression results are given in Table 2. First, it should be noted that subjects are using the cell data in the normative direction. In other words, subjects give positive weight to the A and D cell data and negative weight to B and C cell data. However, it is also obvious that subjects do not attend to cells C and D as strongly as the model suggests. Although all coefficients in equation 1 are significant at the 1% level (one-tailed t test), only cells A and B reach this level of significance in the subjects' judgments (equation 2). (Cell C is marginally significant at the 5% level.)

In a recent paper, Schustack and Sternberg (1981) also used regression equations to test the weight given to each cell's data in a causal reasoning task. They used five different scenarios, estimating regression equations for each scenario. In general, they found all cells to be significant and that cell A was the most important in subjects' judgments. It is interesting that our results do not coincide with theirs, in that the Schustack and Sternberg results show that all the cells, as well as an additional variable proxemic for the impact of alternative causes, do figure significantly in subjects' causal judgments. However, this difference in results may be due to the difference between the task characteristics of their study and the task characteristics of the studies used in this project. One important difference is that Schustack and Sternberg were specifically asking for causal judgments while the 5 studies used as data for this project called for judgments of contingency, causality, or control.

Einhorn and Hogarth (1981), in fact, have hypothesized that questions of causality will focus subjects' attention on cells B and C to a greater extent than will questions regarding contingency. A comparison of Schustek and Sternberg's findings and the results of this study tends to support that claim.

The Lens Model statistics are given in Table 3. Before turning to them, however, we should note that the adjusted R-squared for equation 1, given in Table 2, is .72. This means that 72% of the variance in Y_e is accounted for in the regression equation. It is interesting that such a complex nonlinear function can be well approximated with a linear model and this suggests that using this linear function as a normative model may not be very costly in terms of statistical accuracy. As can be seen in Table 3, subjects' judgments can be fitted fairly well with a linear model; $R_s = \text{corr}[Y_s Y_{s*}] = .67$. In addition, the linear models of the subjects and the "environment" match quite well; $G = \text{corr}[Y* e Y_{s*}] = .96$. It is instructive to compare these values with the average values of such statistics in other lens model studies. Camerer (1981), for instance, did a cross-study analysis of such projects and the average values of the relevant statistics are also listed in Table 3. In general it can be noted that the R_e in this study is higher than average (.87>.64) while R_s is lower than average (.67<.74). However, caution must be exercised in drawing inferences from these comparisons, since most lens model studies ask subjects to predict some noise criterion, while in these studies subjects were predicting the predictability of the criterion. Perhaps predicting a criterion is a more difficult task in that the criterion is observed in a probabilistic, or "noisy,"

environment. Despite this caution, however, it is interesting that the match of the two linear models, equations 1 and 2, is more than .96 as opposed to an average of .56. Also, the subject achievement measure, r_s , for this task is considerably higher than the average in other tasks (.63>.33). Also, R_n for this project is .65 which means that subjects' judgments of correlation are highly correlated (correlation of .65) to actual correlations if we use equation 1 in Table 1, as our model of actual correlation. Another consideration of interest is that R_n and r_s are very close (.65 and .63). This means that subject achievement is practically the same whether we use the complex Pearson's phi equation or a much simpler linear function as our benchmark for subjects' judgments of correlation.

A final result of interest is the significance of the constant term in equation 2 (see Table 2). Although the constant in the \hat{Y}_k equation is not significantly different from zero, the constant term in the subject equation is highly significant (*t* statistic of 4.73) and is close to .5. This suggests that subjects are either using a different judgment scale than they are instructed to use or that they have a priori expectations of a significant degree of covariation. Indeed, Peterson (1980) hypothesized that subjects expect experimental tasks to be 'meaningful' and therefore do not consider the possibility of noncontingency. He suggested that making such a possibility available to subjects would help them recognize noncontingency. Moreover, Peterson was able to empirically demonstrate the accuracy of his hypothesis. In only one of the 5 studies included in this analysis were subjects made aware of the possibility of noncontingency through explicit instructions (Jenkins & Ward). Thus, a general

expectations of consistency may be the reason for a nonzero constant term in the subjects' regression equation. It is also possible, however, that subjects assume that the middle of the judgment scale is the "average" judgment and, thus, use this as a starting point for their judgments. This would suggest the possibility that subjects' judgments may not be sufficiently adjusted away from this .5 starting point. In fact, the variance, or dispersion, of the actual correlations (\bar{Y}_e) in the data used here is significantly greater than the variance of the subjects' judgments (\bar{Y}_s). (F statistic of 3.65 with 30 and 30 degrees of freedom is significant at the 5% level.) Thus, either an anchoring and adjustment heuristic or a priori expectations may account for the constant term in equation 2.

Implications

This study raises several issues. First, it was noted that although cell A is not the only data receiving subjects' attention, it does receive the greatest weight in judgments of covariation. However, this could be due to the form of the covariation question presented to subjects. Crocker (1981b) demonstrated that subjects tend to focus their attention on the cells which are explicitly mentioned in the covariation question. In the studies used as data for this research, the questions focused attention on various cells. The particular cells stressed in each study are listed in Table 1. Note, in particular, that cell A is stressed in each of these studies, and, thus, the importance of cell A in the regression may be due to the question format. However, the apparent importance of cell A could

also be due to variation in subjects' decision rules. Ward and Jenkins (1965), for example, did individual analyses of their subjects and found that commonly used decision rules included the following: $(A/A+B)-(C/C+D)$, $A+B$, and $A/A+B$. Obviously, all of these rules rely heavily on the A cell data and this could drive our results regarding the importance of cell A.

Further research needs to be done to investigate the factors which cause different cells to receive subjects' attention. Many studies, particularly the early ones, assumed that cell A is likely to receive the greatest amount of attention. It would be interesting, however, to delineate the conditions under which this is true. Although there have been contradictory conclusions in the literature regarding subjects' abilities at covariation tasks, only Ward and Jenkins (1965) and Crocker (1981b) have made systematic studies to investigate the reasons for these contradictions.

A second issue raised by this study is whether the statistical model of correlation is an appropriate benchmark to impose on subjects' judgments. The results of Sessie and Endersby's (1972) study, for example, suggest that subjects core well with decision tasks that require covariation assessments when the task does not call for covariation judgments per se. Furthermore, in a classic paper, Taylor and Russell (1939) showed that simply knowing the direction of a relationship can have important effects on decision performance. For example, if college grades and achievement in graduate school are uncorrelated and the base rate of graduate students that are satisfactory is 50%, then even if admissions officers admit only the

10% of their applicants who have the best college records, only 50% of their students will be satisfactory. However, as Taylor and Russell showed, if college grades and graduate performance are correlated only .2, the percentage of satisfactory graduate students rises to .64. With a correlation of .45 this rises to 81%. That is, simply knowing that there is a positive relationship improves the decisions made. It was found, both in this study and in that of Schustack and Sternberg (1981), that subjects do properly sign the cell data. Thus, the direction of the relationship (i.e. positive or negative) was generally correctly inferred. Perhaps this is 'good enough' in the real world where decisions are actually made, and, therefore, use of a model as complex as Pearson's Phi is not necessary.

A further example of this point comes from a replication of Sessie and Endersby's study where subjects were provided with information such as that shown in figure 1. The subjects were asked to decide whether or not to hospitalize a new patient based on the information given about past patients. When the actual correlation of hospitalization and recovery was zero, only 5 or 6 of the 20 subjects chose to hospitalize the patient. With a negative correlation of -.4, no subject chose to hospitalize the patient and the number of subjects choosing hospitalization when the correlation was set at .08 and .19, was 13 and 17, respectively. Thus, it appears that subjects are able to utilize the direction of relationships even when the correlations are rather small in absolute terms.

In summary, this study has provided an overview of human abilities at covariation judgment tasks. Contrary to opinions expressed in the literature, the conclusion is quite positive; subjects appear to do quite well at ascertaining the direction of a relationship, and to use information in the normatively correct direction. Furthermore, this would often seem to be "good enough" in practical circumstances, thus raising questions regarding the normative status of the correlational model as the benchmark for human judgment.

References

- Allow, L. B., & Abramson, L. Y., Judgment of contingency in depressed and nondepressed students: Sadder but wiser?, *Journal of Experimental Psychology: General*, 1979, 108, 441-455.
- Camerer, C., General conditions for the success of bootstrapping models, *Organizational Behavior and Human Performance*, 1981, 27, 411-422.
- Crocker, J., Biased questions in judgment of covariation studies, *Personality and Social Psychology Bulletin*, 1981, in press. (b)
- Crocker, J., Judgment of covariation by social perceivers, *Psychological Bulletin*, 1981, 90, 272-292. (a)
- Einhorn, H. J., & Hogarth, R. M., Uncertainty and causality in practical inference, *Unpublished Manuscript*, University of Chicago, 1981.
- Hursch, C. J., Hammond, K. R., & Hursch, J. L., Some Methodological considerations in multiple-cue probability studies, *Psychological Review*, 1964, 71, 42-60.
- Jenkins, H. M., & Ward, W. C., Judgment of contingency between responses and outcomes, *Psychological Monographs*, 1965, 79, (whole no. 594).

Peterson, C., Recognition of noncontingency, *Journal of Personality and Social Psychology*, 1980, 38, 727-734.

Schustack, M. W., & Sternberg, R. L., Evaluation of evidence in causal inference, *Journal of Experimental Psychology: Gen.*, 1981, 110, 101-120.

Sessie, J. L., & Endersby, H., The empirical implications of Piaget's concept of correlation, *Australian Journal of Psychology*, 1972, 24, 3-8.

Shaklee, H., & Mims, M., Development of rule use in judgments of covariation between events, *Child Development*, 1981, 52, 317-325.

Smedslund, J., The concept of correlation in adults, *Scandinavian Journal of Psychology*, 1963, 4, 165-173.

Taylor, H. C., & Russell, J. T., The relationship of validity coefficients to the practical effectiveness of tests in selection: Discussion and tables, *Journal of Applied Psychology*, 1939, 23, 565-578.

Ward, W. C., & Jenkins, H. M., The display of information and the judgment of contingency, *Canadian Journal of Psychology*, 1965, 19, 231-241.

Example of 2X2 Contingency Table

	Recovered	Did not Recover
Hospitalized patient	A	B
Did not hospitalize patient	C	D

Figure 1

Papers Containing Data Used in this Study

	Number of Data Points	Task Context	Cell(s) stressed
Allou and Abramson (1979)	11	Button Press and Light Onset	A, C
Cordray and Shaw (1978)	4	Test Taking Effort and Performance	A
Jenkins and Ward (1965)	5	Button Press and Light Onset	A, B, C, D
Smetslund (1963)	1	Symptom and Disease	A
Ward and Jenkins (1965)	10	Cloud Seeding and Rainfall	A, D

Table 1

Coefficients and (t-statistics) for Regression Models of
Judged and Actual Correlation

	Constant	Cell A	Cell B	Cell C	Cell D	Adj. R-squared
Y* _e	.162	.0164	-.0225	-.0260	.0182	.72
	(1.24)	(4.76)	(4.22)	(3.92)	(3.61)	
Y*s	.487	.0072	-.0110	-.0088	.0042	.37
	(4.73)	(2.65)	(2.63)	(1.69)	(1.06)	

Table 2

Lens Model Statistics

	This Study	Average
(Camerer, 1981)		
R _e	.87	.64
R _s	.67	.74
G	.96	.56
C	.17	NA
r _a	.63	.33
R _n	.65	NA

Table 3

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Matters
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Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

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ONR Detachment
495 Summer Street
Boston, MA 02210

Mr. R. Lawson
ONR Detachment
1030 East Green Street
Pasadena, CA 91106

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Mr. J. Barber
 HQS, Department of the Army
 DAPE-MBR
 Washington, D. C. 20310

Department of the Navy

Dr. Edgar M. Johnson
 Technical Director
 U. S. Army Research Institute
 5001 Eisenhower Avenue
 Alexandria, VA 22333

Director, Organizations and
 Systems Research Laboratory
 U. S. Army Research Institute
 5001 Eisenhower Avenue
 Alexandria, VA 22333

Technical Director
 U. S. Army Human Engineering Labs
 Aberdeen Proving Ground, MD 21005

Department of the Air Force

U. S. Air Force Office of Scientific
 Research
 Life Sciences Directorate, NL
 Bolling Air Force Base
 Washington, D. C. 20332

AFHRL/LRS TDC
 Attn: Susan Ewing
 Wright-Patterson AFB, OH 45433

Chief, Systems Engineering Branch
 Human Engineering Division
 USAF AMRL/HES
 Wright-Patterson AFB, OH 45433

Dr. Earl Alluisi
 Chief Scientist
 AFHRL/CCN
 Brooks Air Force Base, TX 78235

Foreign Addressees

Dr. Daniel Kahneman
 University of British Columbia
 Department of Psychology
 Vancouver, BC V6T 1W5
 Canada

Foreign Addressees

Dr. Kenneth Gardner
 Applied Psychology Unit
 Admiralty Marine Technology
 Establishment
 Teddington, Middlesex TW11 0LN
 England

Director, Human Factors Wing
 Defence & Civil Institute of
 Environmental Medicine
 Post Office Box 2000
 Downsview, Ontario M3M 3B9
 Canada

Dr. A. D. Baddeley
 Director, Applied Psychology Unit
 Medical Research Council
 15 Chaucer Road
 Cambridge, CB2 2EF England

Other Government Agencies

Defense Technical Information Center
 Cameron Station, Bldg. 5
 Alexandria, VA 22314 (12 copies)

Dr. Craig Fields
 Director, System Sciences Office
 Defense Advanced Research Projects
 Agency
 1400 Wilson Blvd.
 Arlington, VA 22209

Dr. M. Montemerlo
 Human Factors & Simulation
 Technology, RTE-6
 NASA HQS
 Washington, D. C. 20546

Dr. J. Miller
 Florida Institute of Oceanography
 University of South Florida
 St. Petersburg, FL 33701

Other Organizations

Dr. Robert R. Mackie
 Human Factors Research Division
 Canyon Research Group
 5775 Dawson Avenue
 Goleta, CA 93017

Dr. Amos Tversky
 Department of Psychology
 Stanford University
 Stanford, CA 94305

Dr. H. McI. Parsons
 Human Resources Research Office
 300 N. Washington Street
 Alexandria, VA 22314

Dr. Jesse Orlansky
 Institute for Defense Analyses
 1801 N. Beauregard Street
 Alexandria, VA 22311

Professor Howard Raiffa
 Graduate School of Business
 Administration
 Harvard University
 Boston, MA 02163

Dr. T. B. Sheridan
 Department of Mechanical Engineering
 Massachusetts Institute of Technology
 Cambridge, MA 02139

Dr. Arthur I. Siegel
 Applied Psychological Services, Inc.
 404 East Lancaster Street
 Wayne, PA 19087

Dr. Paul Slovic
 Decision Research
 1201 Oak Street
 Eugene, OR 97401

Dr. Harry Snyder
 Department of Industrial Engineering
 Virginia Polytechnic Institute and
 State University
 Blacksburg, VA 24061

Other Organizations

Dr. Ralph Dusek
 Administrative Officer
 Scientific Affairs Office
 American Psychological Association
 1200 17th Street, N. W.
 Washington, D. C. 20036

Dr. Robert T. Hennessy
 NAS - National Research Council (COHF)
 2101 Constitution Avenue, N. W.
 Washington, D. C. 20418

Dr. Amos Freedy
 Perceptronics, Inc.
 6271 Variel Avenue
 Woodland Hills, CA 91364

Dr. Robert C. Williges
 Department of Industrial Engineering
 and OR
 Virginia Polytechnic Institute and
 State University
 130 Whittemore Hall
 Blacksburg, VA 24061

Dr. Meredith P. Crawford
 American Psychological Association
 Office of Educational Affairs
 1200 17th Street, N. W.
 Washington, D. C. 20036

Dr. Deborah Boehm-Davis
 General Electric Company
 Information Systems Programs
 1755 Jefferson Davis Highway
 Arlington, VA 22202

Dr. Ward Edwards
 Director, Social Science Research
 Institute
 University of Southern California
 Los Angeles, CA 90007

Dr. Robert Fox
 Department of Psychology
 Vanderbilt University
 Nashville, TN 37240

Other Organizations

Dr. Charles Gettys
 Department of Psychology
 University of Oklahoma
 455 West Lindsey
 Norman, OK 73069

Dr. Kenneth Hammond
 Institute of Behavioral Science
 University of Colorado
 Boulder, CO 80309

Dr. James H. Howard, Jr.
 Department of Psychology
 Catholic University
 Washington, D. C. 20064

Dr. William Howell
 Department of Psychology
 Rice University
 Houston, TX 77001

Dr. Christopher Wickens
 Department of Psychology
 University of Illinois
 Urbana, IL 61801

Mr. Edward M. Connally
 Performance Measurement
 Associates, Inc.
 410 Pine Street, S. E.
 Suite 300
 Vienna, VA 22180

Professor Michael Athans
 Room 35-406
 Massachusetts Institute of
 Technology
 Cambridge, MA 02139

Dr. Edward R. Jones
 Chief, Human Factors Engineering
 McDonnell-Douglas Astronautics Co.
 St. Louis Division
 Box 516
 St. Louis, MO 63166

Other Organizations

Dr. Babur M. Pulat
 Department of Industrial Engineering
 North Carolina A&T State University
 Greensboro, NC 27411

Dr. Lola Lopes
 Information Sciences Division
 Department of Psychology
 University of Wisconsin
 Madison, WI 53706

Dr. A. K. Bejczy
 Jet Propulsion Laboratory
 California Institute of Technology
 Pasadena, CA 91125

Dr. Stanley N. Roscoe
 New Mexico State University
 Box 5095
 Las Cruces, NM 88003

Mr. Joseph G. Wohl
 Alphatech, Inc.
 3 New England Executive Park
 Burlington, MA 01803

Dr. Marvin Cohen
 Decision Science Consortium
 Suite 721
 7700 Leesburg Pike
 Falls Church, VA 22043

Dr. Wayne Zachary
 Analytics, Inc.
 2500 Maryland Road
 Willow Grove, PA 19090

Dr. William R. Uttal
 Institute for Social Research
 University of Michigan
 Ann Arbor, MI 48109

Dr. William B. Rouse
 School of Industrial and Systems
 Engineering
 Georgia Institute of Technology
 Atlanta, GA 30332

Other Organizations

Dr. Richard Pew
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02238

Dr. Hillel Einhorn
Graduate School of Business
University of Chicago
1101 E. 58th Street
Chicago, IL 60637

Dr. Douglas Towne
University of Southern California
Behavioral Technology Laboratory
3716 S. Hope Street
Los Angeles, CA 90007

Dr. David J. Getty
Bolt Beranek & Newman, Inc.
50 Moulton street
Cambridge, MA 02238

Dr. John Payne
Graduate School of Business
Administration
Duke University
Durham, NC 27706

Dr. Baruch Fischhoff
Decision Research
1201 Oak Street
Eugene, OR 97401

Dr. Andrew P. Sage
School of Engineering and
Applied Science
University of Virginia
Charlottesville, VA 22901

Denise Benal
Essex Corporation
333 N. Fairfax Street
Alexandria, VA 22314

END

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